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PHM INTEGRATION WITH MAINTENANCE AND INVENTORY MANAGEMENT SYSTEMS (PREPRINT)

Fang Tu, Sudipto Ghoshal, Jianhui Luo, Gautam Biswas, Sankaran Mahadevan, Link Jaw, and Kelly R. Navarra

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14. ABSTRACT
Prognostic techniques are intricately tied to the physics of incipient-fault-to-failure progression, and hence most prognostic research has focused on developing techniques for a range of components such as rotating machinery parts. The research and development of such techniques has relied on the theories of material science, structural mechanics, domain expertise, as well as empirical studies such as accelerated run-to-failure testing. Even after prognostic models have been developed and operationally validated for various components of a system, the challenge remains how prognostic assessments from individual components of a system (such as the aircraft engine) should be used to make maintenance and inventory management decisions. In this paper, we describe our research where the primary focus is to bridge the gap between the individual component prognostics and the system-level reasoning required to support maintenance and inventory management decisions. The research involves integration of component health assessment and an information fusion mechanism that operates in conjunction with a higher-level reasoning engine which utilizes system level structural and functional dependencies to generate a system availability analysis that leads directly actionable decision-making tasks for the inventory and maintenance management systems. The inventory management decision systems involve predicting spares requirements and when integrated with remote health monitoring and intelligent diagnostics and prognostics, can assess different spares allocation schemes and optimize inventory management by maximizing system availability within budget constraints.

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PHM Integration with Maintenance and Inventory Management Systems[1,2]

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1. INTRODUCTION

A. Maintenance Management

Current maintenance practices in the world of aviation, in particular the rotating machinery in Air Force on aircraft engines, such as the turbine engine disks, result in the replacement of 99 "good" or working components just to insure against a single "bad" or cracked disk [1]. Since the DoD is increasingly keeping older aircraft and flying them past their originally estimated life, yearly expenditures on replacing the engine disks of older aircraft alone is in excess of $100 million. Considering the false removals, the unnecessary expenditure on working engine disks constitutes $99 million out of the $100 million. Similar statistics are likely for other critical engine components, such as the fan compressor and the blades.

Excessive false removals are only part of the story. The current state-of-the-art on detecting cracks in rotating parts of an engine is primarily through visual inspections and borescope visualizations. Cracks and crack propagation in the fan compressor, blades and disks, chipped or cracked gear teeth are all of serious concern to the aviation industry as well as the DoD. The entire process is predictably rife with false alarms and, on a more dangerous note, could potentially harbor small number of missed detections as well (recall that from a receiver operating characteristic (ROC) analysis, high false alarms are accompanied by smaller missed detections). In those rare cases which may go unnoticed, the result can often be catastrophic.

A well implemented component-level and system-level prognostic system, as shown in the idealized schematic in Figure 1, can alleviate some of the shortcomings identified above. Each intersecting node in the figure represents the health management capabilities of the specific monitoring functions. While many such systems do analyze, detect and

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assess the current health state of the components, of late, only a few of the tools venture into the area of damage prediction and provide actionable recommendations for managing the component. Consequently, systems that utilize information related to material-level prognosis and that can aggregate this information to determine the functional state of the component facilitate a more effective condition-based maintenance scheduling than time-based preventive maintenance scheduling practiced today. This also results in better utilization of the component and significantly reduced false removals.

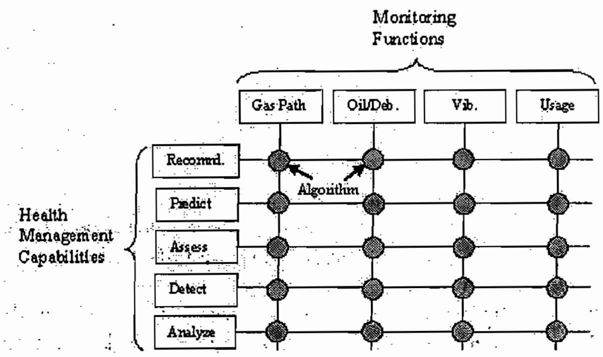


Figure 1: Algorithmic view of a comprehensive PHM (Prognostic Health Management) solution. In this case, the monitoring functions depicted are relevant to an aircraft engine.

A prognostic system that drives an improvement in the maintenance management typically will require integration of three essential capabilities – physics-based health and damage propagation modeling, adequate non-invasive mechanisms to determine the appropriate quantitative knowledge that leads to health assessment and an information fusion mechanism that operates in conjunction with a higher-level reasoning engine.

B. Inventory Management

Inventory management in the aviation industry is challenging due to the following difficulties [2]:

- High Inventory Value - Aviation equipment is highly-specialized with expensive spare parts; therefore, holding those parts in inventory to ensure system availability can result in enormous inventory costs.
- Distributed Vendors - Outsourcing service to third-party aviation vendors is common; hence collaborative planning, global visibility and service coordination among multiple vendors are essential.
- Fleet Availability Targets - In addition to fill rate for spares, service organizations must be able to meet fleet availability targets.
- Sporadic and Intermittent Demand - Causal factors such as operating hours and operating conditions result in high demand variability. Without reliable demand histories, it is difficult to calculate the probability of failure events.
- Procurement Lead-Time Variability - Spare parts for aircraft systems often have long lead-times, making spares optimization difficult.

Despite the difficulties in establishing an efficient inventory management for such complex and dynamic systems, the return on investment is high. AeroStrategy's analysis [3] suggests inventory worth $44 billion is now held in the air transport MRO (Maintenance, Repair, and Overhaul) supply chain, supporting nearly 17000 aircraft. This implies that about $2.5 million worth of inventory is available for each aircraft. It is easy to see that significant cost savings can be achieved through efficient inventory management by a mere 5% improvement.

It has been shown that utilizing information about the demand and inventory activities and incorporating them in day-to-day decision-making in supply chain management will help us achieve better material flow and on-time deliveries [4]. However, due to the need for significant human involvement, the information needed for demand forecasting is very often buried in large volumes of operational and maintenance data collected and left unutilized. Therefore, it will be especially beneficial if we possess the automated reasoning capabilities to identify potential problem systems or components; update repair times and failure rates from maintenance log data or operational data; and use such diagnostic and prognostic information for inventory management.

In this paper, we demonstrate a seamless process, in which we utilize the material-level health assessment and damage prognosis, and the system level structural and functional dependencies to generate a subsystem or component prognostic analysis that leads to directly actionable decision-making tasks for spares allocation and inventory management. A system, as described above, when effectively implemented, can enhance the ability of decision-makers to efficiently deploy and manage their assets in rapidly evolving combat situations where demands on the component can be intense and stressful.

C. Scope and Organization of the Paper

The paper is organized as follows. Section 2 outlines a smart-service concept in which diagnostic and prognostic reasoners work hand-in-glove with the inventory management module for planning maintenance actions and replenishing supplies preemptively. Section 3 describes a model-based prognostic process and reports on a demonstration of the prognostic procedure on a generic centrifugal pump system. In Section 4, we describe a simulation-based approach to system availability analysis, and demonstrate an integrated process in which the updated residual life predictions obtained from prognostics are used to forecast service demand and to assess the efficacy of different spares allocation schemes in maximizing system availability using an engine system as an example. Section 5 concludes the paper with summary and future research directions.

2. CONCEPT FOR A "SMART SERVICES" SOLUTION

Figure 2 depicts our concept of how an inventory management module can be deployed and integrated with diagnostics and prognostics to provide smart services, i.e., planning maintenance actions and replenishing supplies preemptively, rather than retroactively. Unlike conventional maintenance strategies, prognostic techniques predict component degradation based on observed system condition to support "just-in-time" maintenance. The ever increasing usage of model-based diagnosis and prognosis of systems facilitates the integration of model-based diagnosis and prognosis of systems, leading to condition-based spares management and maintenance. In the proposed architecture, the demand forecasting and inventory management module incorporates updates on system operating conditions and health information collected and inferred by a diagnosis and prognosis server. The functions of the blocks developed in this paper are discussed in greater detail below, while the spares allocation optimization module will be included in our future research.

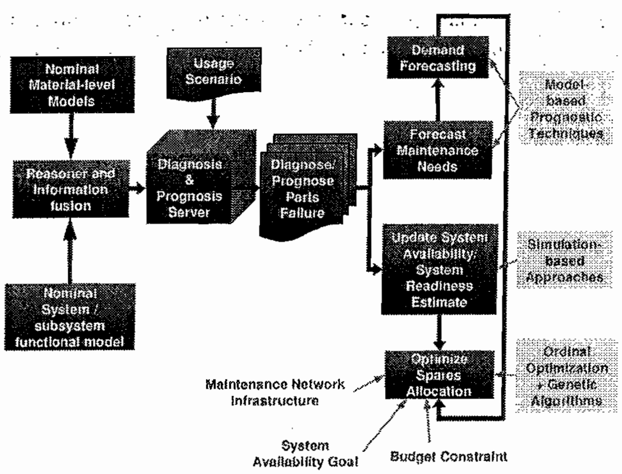


Figure 2: Concept for a "Smart Services" Solution Supported by Diagnostics and Prognostics

A. Demand Forecasting

Demand for spares cannot be easily gauged because the consumption of spares is event-based and therefore is probabilistic in nature. The events themselves can be scheduled (planned) or unscheduled (unplanned). Scheduled maintenance, system overhauls, etc., would fall in the first category, whereas random breakdowns would be in the second category. The intermittent nature of spare part demand due to breakdowns makes it impossible to apply conventional time series based algorithms. Moreover, since the real operating conditions of a component usually differ from assumed ones, discrepancies arise between specified constant mean-time-to-failure and true residual life time. Predictions of residual life time and their variances based on observed environment (e.g., temperature, humidity and dust) and operating conditions (e.g., vibration and pressure) or historical/field data have inherently much higher quality than constant mean-time-to-failure data. Model-based prognostic approaches are applied to obtain component degradation profiles, estimate the consequences of such degradations on system performance variables, and dynamically evolve the residual life time prediction based on the load and environmental conditions.

The main idea is to move away from traditional demand-driven forecasting that relies on a time-based scheduled maintenance approach to condition-based forecasting using remaining life predictions of components. We describe a model-based prognostic approach in section 3 for computing the remaining useful life of a component.

B. System-level Availability Estimation

After obtaining the remaining useful life estimation using model-based prognostic approaches, we perform system-level availability analysis to evaluate the performance of each candidate spares allocation scheme. The system availability analysis methodology is hierarchical and comprises of models at two tiers: At the lower tier is a component-level model that considers the impact of spares on component availability. At the higher tier is a system-level model that considers the impact of system architecture, mission phases, and different system configurations over mission phases on system availability. The component availabilities computed from the lower tier models are propagated to the higher tier model to enable the computation of system availability. The details of system availability analysis approach will be described in Section 4.

3. MODEL-BASED PROGNOSTIC TECHNIQUES

A. Approach

The model-based prognostic approaches are applicable in situations where accurate mathematical models can be constructed from first principles. These methods use residuals as features, where the residuals are the outcomes of consistency checks between the sensed measurements of a system and the outputs of a mathematical model. The premise is that the residuals are large in the presence of malfunctions, and small in the presence of normal disturbances, noise and modeling errors. Statistical techniques are used to define the thresholds to detect the presence of faults. The three main ways of generating the residuals are based on parameter estimation, observers (e.g., Kalman filters, reduced order unknown input observers, Interacting Multiple Models [7]) and parity relations.

Figure 3 illustrates our adaptive model-based prognostic process [6]. In this process, first, a system degradation model is identified and data from model-based simulations under nominal and degraded conditions are collected. Oftentimes, simulation tools have already been developed, such as the TRICK simulator for the orbital maneuvering system/reaction control system of NASA spacecraft and the STORM model for P&W engines; then we can use these tools directly to obtain operational data under different usage profiles.

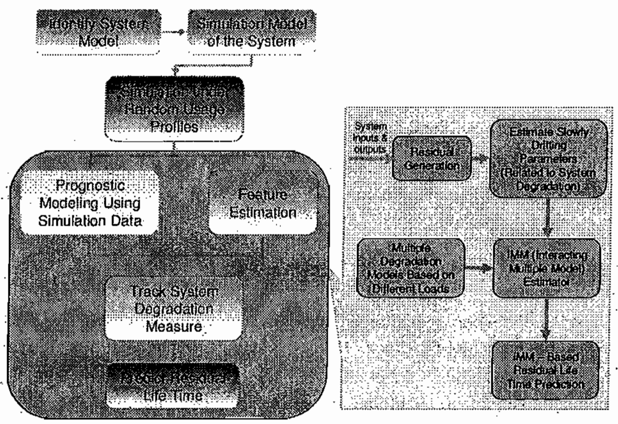


Figure 3: A Model-based Prognostic Process

Because of the continuously changing nature of an abnormal condition, the severity of a fault increases with the usage of the system. This change in fault severity over time forms a trajectory of degradation, which is dependent on the usage profiles (environmental and operating conditions). Therefore, in the second step of the process, prognostic models based on different random usage profiles and conditions (termed modes) are constructed. Third, the Interacting Multiple Model (IMM) approach is used to track the hidden damage to make the prognosis adaptive to the current usage profile, while remaining useful life prediction is performed by mixing mode-based life predictions via time-average mode probabilities. A by-product of this process is the prediction of *Time to Criticality*, defined as the time from the indication of a fault or degradation of a function to the complete failure of that function. Comparing this measure with the *Time to Remediate* will offer us insights into whether a catastrophic system failure can be confidently prevented. The solution proposed here is generic and has the potential to be applicable to a variety of aviation systems and their components. The main advantage of such a model-based prognostic process over data-driven approaches is its ability to incorporate a physical understanding of the system for monitoring. Another advantage is that, in many situations, the changes in feature vector are closely related to model parameters. Therefore, it can also establish a functional mapping between the drifting parameters and the selected prognostic features. Moreover, as understanding of the system degradation improves, the model can be adapted to increase its accuracy and to address subtle performance problems. Thus, our approach may be viewed as a Bayesian approach to prognosis, as opposed to a Maximum likelihood approach based purely on data.

As illustrated in Figure 3, our adaptive model-based prognostic process consists of six steps for predicting the residual life time of a component/system. The details of each step can be found in [6]. In Section B.2, we demonstrate the six-step prognostic process using an example scenario.

B. Application to an Example System

In this section, we study the system model of a generic centrifugal pump system and predict the residual lifetime of the system using the process elaborated above.

B.1 Basic Principles of a Generic Centrifugal Pump

The purpose of a centrifugal pump is to convert the energy of an electric motor or engine into kinetic energy, and then into pressure of a fluid that is being pumped. Figure 4 illustrates the operation of a centrifugal pump.

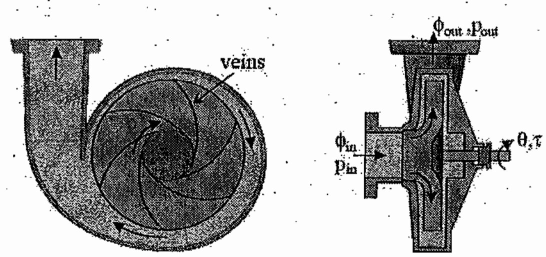


Figure 4: Operation of a Centrifugal Pump

The simplified physical model of a centrifugal pump is derived using conservation of power and momentum. The corresponding equation is

$$\tau.\theta = p_{out}.\phi_{out} \quad (1)$$

where τ is the input torque, θ represents angular velocity of the pump rotor, p_{out} is the pump pressure, and ϕ_{out} is the corresponding mass flow rate.

Conservation of momentum states that the mechanical momentum $\int \tau.dt$ equals the hydraulic momentum. The coefficient of transmission of the gyrator model includes two parameters, *a* and *b*, that represent the cross sectional area and curvature of the veins. The amount of mass moved by the pump depends on the total area of its vanes, *a* minus the effective loss in moved mass due to the curvature of the vanes, *b*. This is given as $\int (a.\theta - b.\phi_{out}).dt$.

The hydraulic momentum of the pump is represented by $\phi_{out} \int (a.\theta - b.\phi_{out}).dt$. Therefore

$$\int \tau . dt = \phi_{out} \int (a.\theta - b.\phi_{out}).dt \quad (2)$$

Eq. (2) can be rewritten as:

$$\tau = \phi_{out}(a.\theta - b.\phi_{out}) + \dot{\phi}_{out} \int (a.\theta - b.\phi_{out}).dt \quad (3)$$

which for relatively low flow accelerations compared to flow velocity, yields the constituent relation $\tau = \phi_{out}(a.\theta - b.\phi_{out})$. This yields

$$p_{out} = (a.\theta - b.\phi_{out})\theta \quad (4)$$

Eq. (4) describes a modulated gyrator with modulus $(a.\theta - b.\phi_{out})$.

B.2 Component-level Degradation Model

The analysis done here is only to explore the feasibility of applying the methodology described in Section 3.A for residual life prediction of the pump system. Therefore, a simplified physical model of the pump is used instead of complex finite element models. The flow in the system is assumed to be steady and the computational fluid dynamics model is not used. Future application may require advanced numerical simulation instead of the current simplified model. The goal for this part of the methodology is to link the possible causes of the fault, established at the system level (e.g., change in transmission efficiency from motor to pump, possible change in surface area of pump vanes, and increase in resistance parameter) to root causes that are defined by physics of failure models. An example failure scenario is illustrated below. Identification of a root cause enables one to link mathematically the effect of damage at the material and structural level to rate of change of system level parameters. Studying these rates and simulating system behavior and performance using these rates, provide a framework for predicting the residual lifetime of the system.

<u>*An Example Scenario: Corrosion/erosion damage to vanes*</u>

Corrosion/erosion damage removes material from components, such as vanes in the current example. A schematic picture of this type of damage is shown in Figure 5. The corrosion/erosion damage may change the vane surface and reduce the total area of vanes in moving flow. Also, the irregular surface of vanes may cause turbulence in the pump and reduce the efficiency in moving flow. All these effects can be considered as loss of vane area (a).

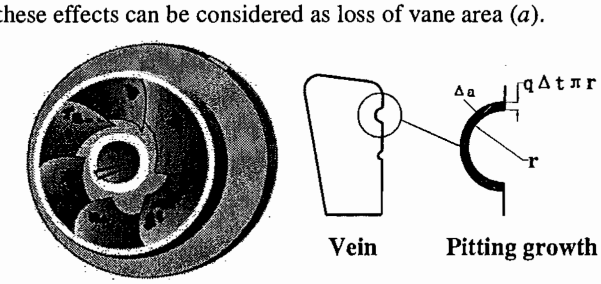


Figure 5: Schematic corrosion/erosion damage to the vanes (left) and schematic pitting growth model (right)

To calculate the area loss due to corrosion, detailed local flow analysis and dissolution mechanism are required. A simple calculation is shown here for illustrative purpose under simplified assumptions.

<u>*Step 1: Identify system model*</u>

The corrosion rate $\dot{q}$ of vane material is taken from [13] as

$$\dot{q} = K(c_s - c_b) \quad (5)$$

where K is the mass transfer coefficient dependent on the flow velocity, c_s is the corrosion product concentration at the liquid-solid interface dependent on the local temperature, and c_b is the concentration in the bulk flow and is often set to zero [13]. We assume constant flow velocity and temperature, and same concentration in the liquid. Thus, $\dot{q}$, K and c_s are constants.

Further, we assume the corrosion damage to the vane occurs at the edge. The vane area loss is due to edge pitting growth. The growth pattern is assumed to be circular, as shown in Figure 5 (right).

The area loss at one pitting location can be expressed as

$$\Delta a_i = \dot{q}\pi r \Delta t = \dot{q}\pi\dot{q}t\Delta t \quad (6)$$

Integrating Eq. (6) over time, we obtain the area loss at one pitting location as a function of time t, as plotted in Figure 6. The total vane area loss Δa can be expressed as

$$\Delta a = \sum_{i=1}^{n} \Delta a_i = \frac{1}{2}\pi\zeta^2 t^2$$
$$\zeta^2 = (c_s - c_b)^2 \sum_{i=1}^{n} K_i^2 \quad (7)$$

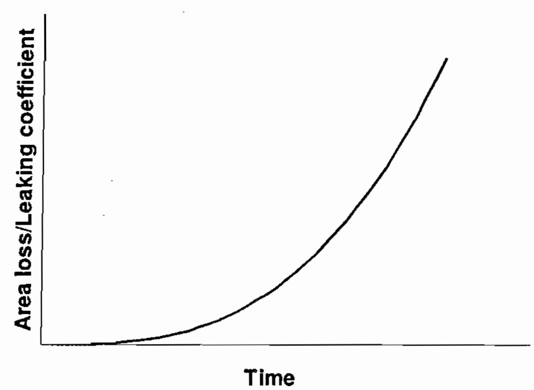


Figure 6: Schematic Plot of Area Loss Function

At a time instant t_1, the pump pressure and flow rate can be expressed as

$$p^*_{out} = (a^*.\theta - b.\phi^*_{out})\theta \quad (8)$$

where the superscript * indicates the quantity is at the time instant t_1. Based on the first order perturbation theory, these quantities can be expressed as

$$\begin{cases} p^*_{out} = p_{out} + \Delta p \\ \phi^*_{out} = \phi_{out} - \Delta \phi \\ a^* = a - \Delta a \end{cases} \quad (9)$$

Substituting Eq. (9) into Eq. (8), we obtain

$$p_{out} + \Delta p = a\theta^2 - \Delta a\theta - b\phi_{out}\theta + b\Delta\phi\theta \quad (10)$$

Substituting Eq. (4) into Eq. (10) and solving for Δa, we obtain

$$\Delta a = \frac{b\Delta\phi\theta - \Delta p}{\theta^2} \quad (11)$$

where Δa, $\Delta\phi$ and Δp are all functions of t during the entire service life of the pump system.

Eq. (3) consists of fast-time dynamic equation and measurement equation. To construct a complete prognostic model, we need a slow-time model for the degradation measure ξ. In this model, we assume that the area loss of the vanes during one simulation episode i, $\Delta\alpha_i$, is a function of ξ, the area loss at the beginning of the episode (α_i), and the load during this episode, in the form of

$$\Delta\alpha_i = 0.1 \cdot (\pi\alpha_i) \cdot \sum_{j=1}^{n_i} (p_i^j)^2 \cdot [1.122 - 1.4(\alpha_i / a)^2 + 7.33(\alpha_i / a) - 13.08(\alpha_i / a)^3 + 14(\alpha_i / a)^4]^2 \quad (12)$$

where n_i is the cycle number and $\{p_i^j\}_{j=1}^{n_i}$ is the load parameter, both of which are obtained via some cycle counting approaches, such as rainflow, mean-crossing, etc. [10] based on the stress/strain/load information during the episode, which is assumed to be a function of ϕ_{out}. In this paper, we adopt the most commonly used cycle counting method, viz., the rainflow method. This method is able to catch both slow and rapid variations of load by forming cycles that pair high maxima with low minima, even if they are separated by intermediate extremes [14]. We assume that the maximum α is $a/4$ and define the degradation measure as $\xi = 4\alpha / a$. Apparently, $\xi = 1$ marks the end of life for the pump.

Step 2: Simulation results

The system model in Eq. (3) was simulated with a standard 4th-order variable-step-size Runge-Kutta method. Figure 7 shows the results of 100 Monte-Carlo simulations for the pump system under three different load conditions, with the input torques equal to 2000, 2500, and 3000 *Nm*, respectively, and the angular velocity is set at 165 *rad/s* for all three modes. The nominal cross sectional area of the pump, $a = 0.3m^2$. The perturbations are added to the inputs, i.e., the torque and the angular velocity, in the form of a Gaussian noise with zero mean and variances that are set to make the signal-to-noise ratio (SNR) equal to 1 in all three modes. From Figure 7, we can see that compared to the severely overloaded condition, the increases in the life times for the overloaded and normal conditions are about 40% and 140%, respectively. If we assume a 50% calendar time usage of the pump system (12 hours a day), the expected life of the pump system will be approximately 3.8, 5.4, and 9.2 years, respectively, for the three load conditions (severely overloaded, overloaded and normal).

Step 3: Prognostic modeling from simulation data

Since the pump system has three random load conditions, the number of modes in the degradation model is 3. The model parameters for each mode can easily be estimated from the Monte-Carlo simulations as described in [6].

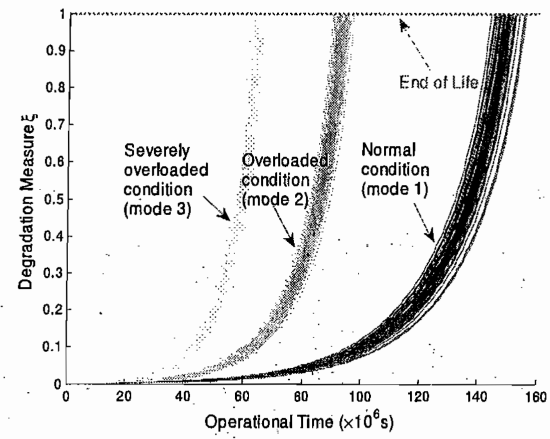


Figure 7: 100 Monte-Carlo Simulations for 3 Random Loads

Step 4: Feature estimation

The hidden variable ξ is estimated from the input/output data, i.e., input torque, input angular velocity and output flow rate, through linear least-squares estimation by minimizing the sum of square error between the estimated output and the actual measurement over the observation period.

Step 5: Track the degradation measure

For IMM implementation, we use the following transition matrix:

$$\Phi = \begin{bmatrix} 0.9 & 0.05 & 0.05 \\ 0.05 & 0.9 & 0.05 \\ 0.05 & 0.05 & 0.9 \end{bmatrix}$$

where ϕ_{ij} =P(mode j in effect at time k+1|mode i in effect at time k). The system mode changes are simulated as follows. Mode 1: [0, $40\times10^6 s$], Mode 2: [40, $80\times10^6 s$], Mode 3: [80, t_{end}], where t_{end} is the time at which $\xi = 1$.

Figure 8 shows the plot of mode probabilities of the IMM. The mode probabilities for the three modes are initialized to ($\bar{\mu}_j(0) = 1/3, j = 1,2,3$) and then Mode 1 reaches the highest mode probability (approximately 0.80~0.90) in the range [0,

$40\times10^6 s$]. Mode 2 reaches the highest mode probability (approximately 0.90~1.0) in the range [40, $80\times10^6 s$]. Finally, Mode 3 dominates the remainder of simulation with the highest probability of around 1. Thus, the IMM (which may be viewed as a software sensor) tracks the load conditions very well based on noisy data.

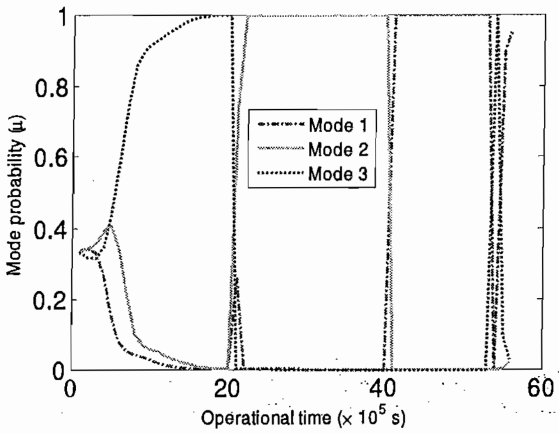


Figure 8: Mode Probabilities of the IMM

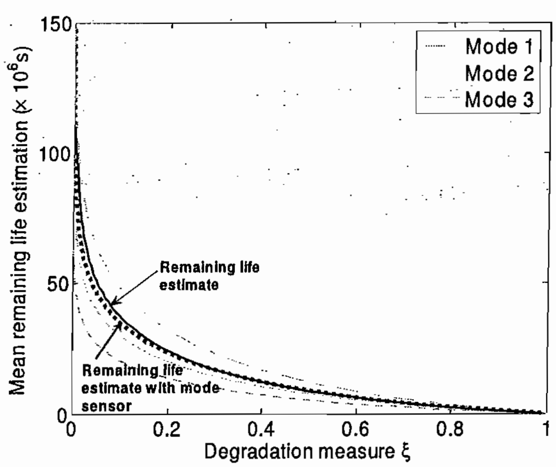


Figure 9: Estimate of remaining life for a single run

Step 6: Predict the Remaining Life

Figure 9 presents the estimate of residual life (solid line) using IMM mode probabilities for a single run of the scenario considered in *Step 5*. We can see that, initially, the residual life estimate follows Mode 1 and after switching to Mode 2, the residual life estimate is in between those of Modes 1 and 2, which is what one would expect. Finally, the residual life estimate approaches that corresponding to Mode 2. The dashed bold line represents the residual life estimates assuming that the load condition can be measured accurately via a sensor. In such a case, the current mode is known. We can evaluate the contribution of the additional sensor to the accuracy of the residual life estimate. In Figure 9, we can see that the IMM produces residual life estimates that are very close to the estimates that one would get with the additional sensor. The difference between these two estimates is relatively high (about 10%) at the beginning ($\xi < 0.2$), and they are virtually identical as degradation measure ξ increases.

4. SPARES ALLOCATION ASSESSMENT

A. System Availability Analysis Approach

The system availability analysis methodology comprises of both component-level and system-level analyses.

A. 1 Component-level Model:

We describe the lower tier component-level availability model in this section. Assume that the time to failure of a component is exponentially distributed. When a component fails, it is replaced immediately with a spare if a spare is available. However, if a spare is not available, then additional spares need to be procured for replacement. The repair times, both with and without the availability of spares are assumed to be exponentially distributed. For component i, let:

s_i – Number of spares.
λ_i – Failure rate.
μ_i – Repair (replacement) rate when a spare is available.
γ_i – Repair (replacement) rate when a spare is not available.

p_k – Probability that k spares are obtained to rebuild inventory.

Figure 10 shows the Markov model of the failure and repair process of a component in the presence and absence of spares. In the model, the state is described by a 2-tuple (c,d), where c is the number of spares available in the inventory and d indicates whether the component is operational or failed. Thus, c ranges from s_i to 0 and d can take two values, namely, U (Up) and D (Down). The component starts in state (s_i,U) where all the s_i spares are available and the component is operational. From this state, the component can transition to state (s_i,D) with rate λ_i upon the failure. From the state (s_i,D), a transition occurs to state (s_i-1,U) with rate μ_i, when the failed component is replaced by an available spare. This continues until state $(0,U)$ is reached in which the component is operational, but no additional spares are available. A failure in this state causes a transition to state $(0,D)$ with rate λ_i. In the state $(0,D)$, since no spares are available, additional spares need to be procured. It is certainly necessary to obtain one component to replace the failed one. In addition, extra spares may be obtained to rebuild the inventory of spares. With probability p_k, additional spares are obtained, where k ranges from 0 to s_i. As a result, from the state $(0,D)$, transition to state (k,U) can occur with rate $\gamma_i p_k$.

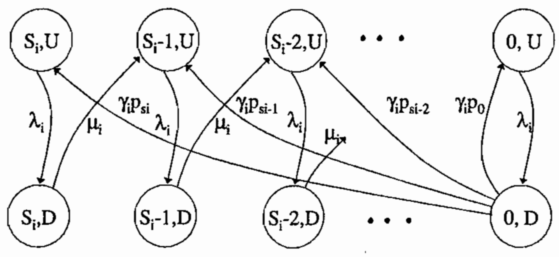


Figure 10: Component-level Availability Model

A. 2 System-level Model:

The system availability model at the higher tier of the hierarchy is described in this section. In the base scenario, all the components of the system are active when the system is operational. In this case, the system may be considered to have just one phase and the components of the system may be organized into a series, parallel, *k*-of-*n* or a combination of these structures. A reliability block diagram may be an adequate system availability model in this case.

For some systems, execution may proceed through phases, and not all components are active/operational in all phases. For such a system, the phased execution may be modeled as a continuous time Markov chain, with the state space given by the phase of system execution. Let m denote the number of phases, with the sojourn time in each phase exponentially distributed. We let τ_l denote the parameter of the exponential distribution of sojourn time in phase l. Further, we let $w_{l,r}$ denote the probability that the system transitions from phase l to phase r, with l and r ranging from 1 through m.

A. 3 Computation of System Availability

Most of the efforts in evaluating highly dependable systems are limited to analytical or numerical solutions, usually restricted to Markov models. The applicability of these techniques, however, is hindered by practical problems, such as state-space explosion of Markov representations of real systems. Because the number of states in Markov models usually grows exponentially with the number of system components, and because of storage and computational limitations, only relatively small systems can be analyzed using numerical solution techniques.

When conventional analytical/numerical methods are no longer feasible, analysts often turn to computer simulation, with the obvious advantages of flexible representation of complex systems at the desired level of abstraction and low storage requirements. However, the accurate estimation of availability using simulation requires frequent observations of the system failure event, which by definition are rare events in highly-dependable systems. This renders conventional simulation impractical for evaluating such systems. To solve this problem, there have been considerable and successful efforts to develop fast simulation techniques based on Importance Sampling. The basic idea of Importance Sampling is quite simple: simulate the system using new probability-dynamics (different from the original probability-dynamics of the system), so as to increase the probability of typical sequences of events leading to system failures. The obtained availability measure in a given observation is then multiplied by a correction factor called the "likelihood ratio" to yield an *s*-unbiased estimate of the measure. Appropriate and careful choice of the new underlying probability dynamics of the simulated system can yield an appreciable reduction in the variance of the resulting estimate, which implies appreciable reduction in the simulation time needed to achieve a specified precision [5].

The methodology of applying the Importance Sampling approach to estimate the system availability with spares information is outlined in [17].

B. A Case Study

In this section, we apply the techniques described above to evaluate and compare different spares allocation schemes. In this study, we obtained a Detailed Maintenance Data report generated for Type Equipment Code (TEC) code AMAF and Work Unit Code (WUC) "27%" (F/A-18 Engine System) during 10/01/05 - 10/10/06 from Navy's DECKPLATE (Decision Knowledge Programming for Logistics Analysis and Technical Evaluation) data warehouse. This report records for each BuSer (Bureau Serial No.) the maintenance action taken, the WUC, the maintenance level, the man hours spent, the type of maintenance, the removed part No., as well as the installed part No. Out of the 10930 entries, we notice that the WUCs with prefix "2747" have the most entries. Therefore, we chose the engine subsystem and its components with WUCs of the form "2747*" to build a conceptual TEAMS [15]-[16] hierarchical model for demonstration.

The TEAMS model, as shown in Figure 12, consists of 31 components, corresponding to the WUC code list with prefix "2747" obtained from Navy's CMIS (Configuration Management Information System) system. The components with the longest WUC codes are at the bottom level of the hierarchy. The mean-time-to-repair for each component is estimated based on the man hours spent, as entered in Figure 13, while the failure frequencies are used as estimates of the failure rates. Figure 11 shows a pivot chart of the failure frequencies as recorded in the report. The chart shows that the Anti-icing Valve (WUC 2747D) has the most entries during the reporting period. For this study, its failure rate was set to be 0.0001, while all the other components were assigned lower failure rates proportional to their failure frequencies as recorded in the report. In general, all components were assumed to be single points of failure (series arrangement in the reliability block diagram); however, to demonstrate the ability to handle other system configurations, some redundant configurations have also been assumed in the model, as shown in the small block in Figure 12.

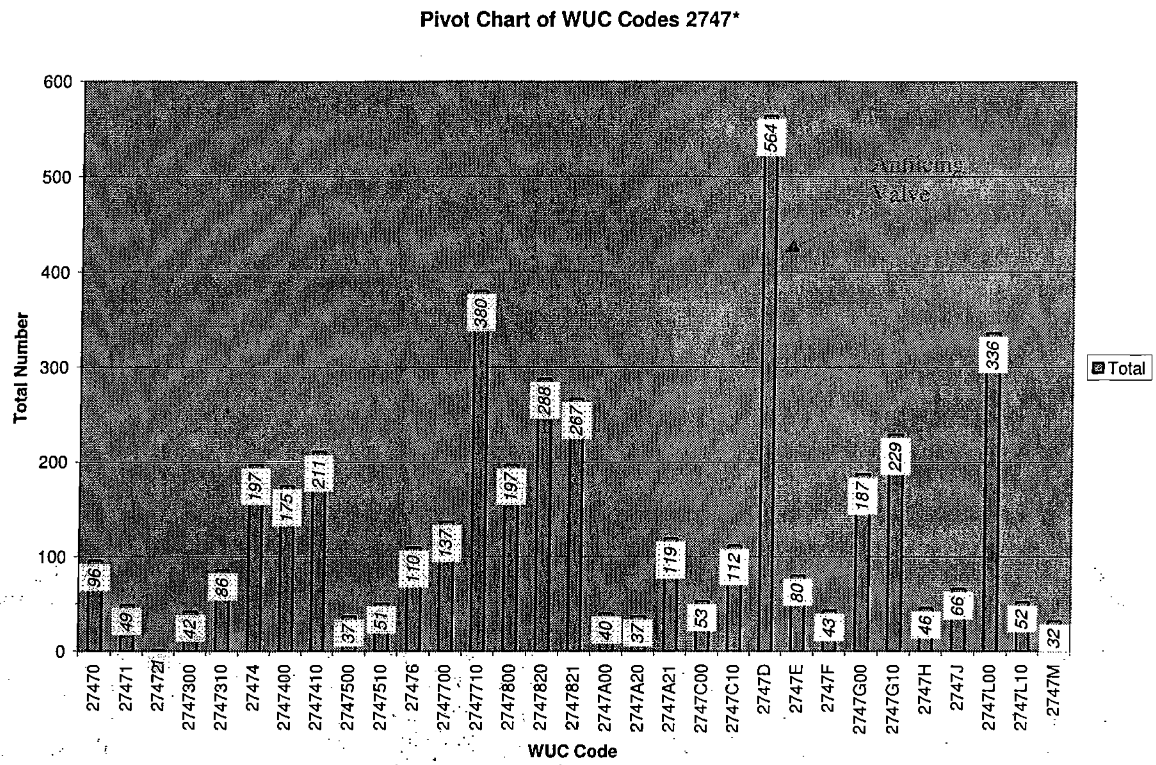


Figure 11: Pivot Chart of Maintenance Records with WUC Codes "2747*"

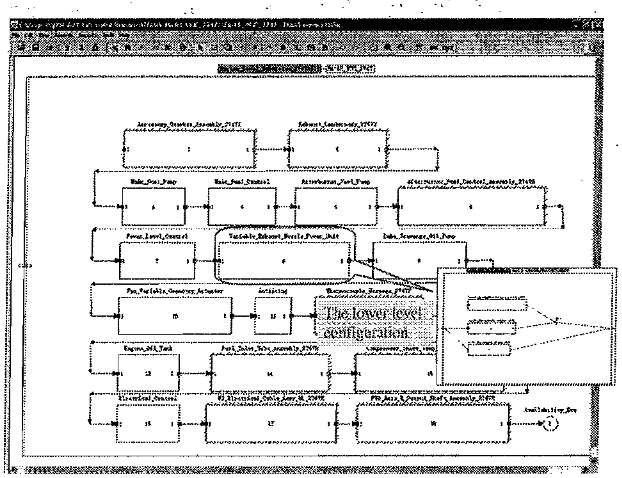


Figure 12: A Conceptual Hierarchical TEAMS Model for Engine Components with WUC Codes "2747*"

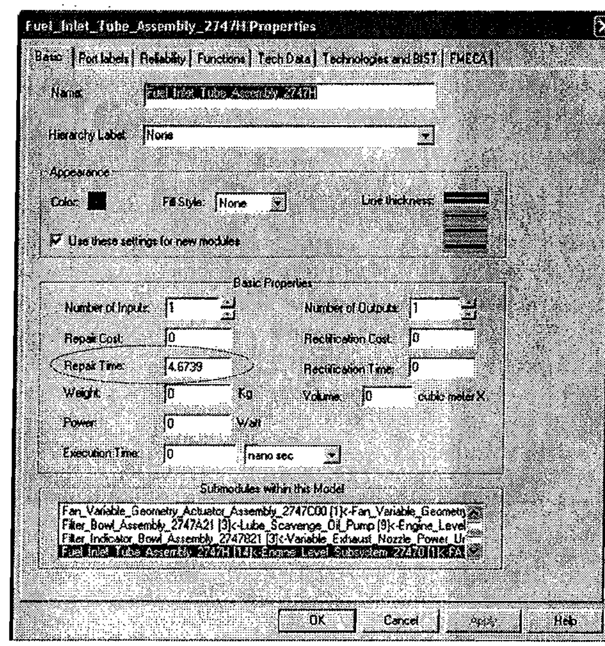
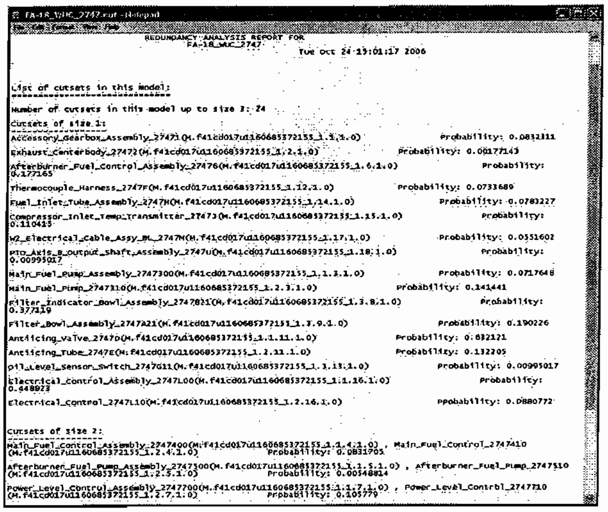


Figure 13: Mean Time to Repair Estimated from the Maintenance Records


FA-18_WUC_2747.out - Notepad

REDUNDANCY ANALYSIS REPORT FOR
FA-18_WUC_2747
Tue Oct 24 15:01:17 2006

List of cutsets in this model:

Number of cutsets in this model up to size 3: 24

Cutsets of size 1:

Accessory_Gearbox_Assembly_27471(M.f41cd017u1160685372155_1.1.1.0) Probability: 0.0832311
Exhaust_Centerbody_27472(M.f41cd017u1160685372155_1.2.1.0) Probability: 0.00177143
Afterburner_Fuel_Control_Assembly_27476(M.f41cd017u1160685372155_1.6.1.0) Probability: 0.177165
Thermocouple_Harness_2747F(M.f41cd017u1160685372155_1.12.1.0) Probability: 0.0733689
Fuel_Inlet_Tube_Assembly_2747H(M.f41cd017u1160685372155_1.14.1.0) Probability: 0.0783227
Compressor_Inlet_Temp_Transmitter_2747J(M.f41cd017u1160685372155_1.15.1.0) Probability: 0.110415
W2_Electrical_Cable_Assy_BL_2747M(M.f41cd017u1160685372155_1.17.1.0) Probability: 0.0551602
PTO_Axis_B_Output_Shaft_Assembly_2747U(M.f41cd017u1160685372155_1.18.1.0) Probability: 0.00995017
Main_Fuel_Pump_Assembly_2747300(M.f41cd017u1160685372155_1.1.3.1.0) Probability: 0.0717648
Main_Fuel_Pump_2747310(M.f41cd017u1160685372155_1.2.3.1.0) Probability: 0.141441
Filter_Indicator_Bowl_Assembly_2747821(M.f41cd017u1160685372155_1.3.8.1.0) Probability: 0.377119
Filter_Bowl_Assembly_2747A21(M.f41cd017u1160685372155_1.3.9.1.0) Probability: 0.190226
Antiicing_Valve_2747D(M.f41cd017u1160685372155_1.1.11.1.0) Probability: 0.832121
Antiicing_Tube_2747E(M.f41cd017u1160685372155_1.2.11.1.0) Probability: 0.132205
Oil_Level_Sensor_Switch_2747G11(M.f41cd017u1160685372155_1.1.13.1.0) Probability: 0.00995017
Electrical_Control_Assembly_2747L00(M.f41cd017u1160685372155_1.1.16.1.0) Probability: 0.448923
Electrical_Control_2747L10(M.f41cd017u1160685372155_1.2.16.1.0) Probability: 0.0880772

Cutsets of size 2:

Main_Fuel_Control_Assembly_2747400(M.f41cd017u1160685372155_1.1.4.1.0) , Main_Fuel_Control_2747410 (M.f41cd017u1160685372155_1.2.4.1.0) Probability: 0.0831705
Afterburner_Fuel_Pump_Assembly_2747500(M.f41cd017u1160685372155_1.1.5.1.0) , Afterburner_Fuel_Pump_2747510 (M.f41cd017u1160685372155_1.2.5.1.0) Probability: 0.00548814
Power_Level_Control_Assembly_2747700(M.f41cd017u1160685372155_1.1.7.1.0) , Power_Level_Control_2747710 (M.f41cd017u1160685372155_1.2.7.1.0) Probability: 0.105779

Figure 14: Redundancy Analysis Report Showing the List of Minimal Cut Sets and Their Probabilities at 10000 Hours

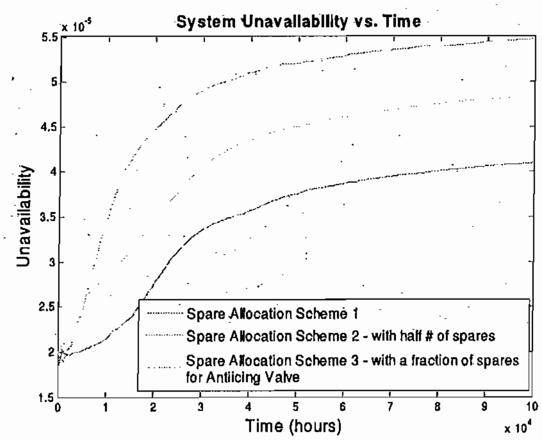


Figure 15: Plot of System Unavailability vs. Time for Different Spares Allocation Schemes

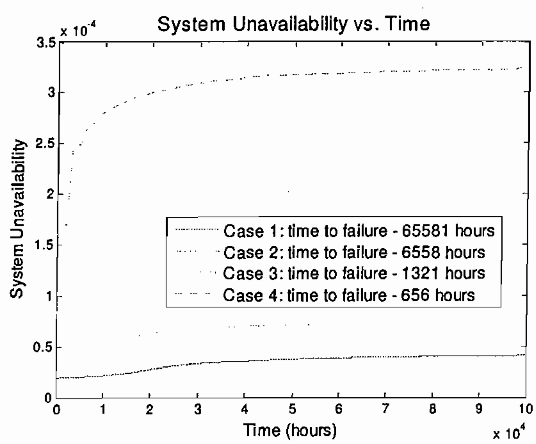


Figure 16: Plot of System Unavailability vs. Time for Different Residual Life Estimates

After the conceptual engine component model was built in TEAMS, various types of analysis, such as redundancy analysis and reliability analysis, were performed. Redundancy analysis generates a list of minimal cut sets based on the TEAMS model and calculates the probability of each minimal cut set at the user-defined mission time. Figure 14 shows the redundancy report generated for the engine component model. There are 24 minimal cut sets in this model, out of which 17 are singletons (cut sets of size 1) and 7 are doubletons (cut sets of size 2). The list of minimal cut sets, the list of components and their failure rates, mean-time-to-repair, etc., are output to the spares analysis module to estimate, for a spares allocation scenario, how the system level availability evolves over time. We simulate two scenarios, one for different spares allocation schemes and the other for different residual life time predictions for the main fuel pump. In the simulation, the mean-time-to-repair when the spares are out-of-stock is set to be 10 times the mean-time-to-repair when the spares are in stock. The repair time is assumed to be exponentially distributed.

Figure 15 shows the system unavailability curves for three different spare allocation schemes. In the first scheme, we assume that the number of spares allocated to each component is proportional to its failure rate, i.e., the component that fails the most frequently gets the most spares. The component that fails the most in the system, i.e., the Antiicing Valve, gets 20 spares when the stock is being replenished. In the second scheme, every component gets only half the number of spares as in the first scenario. Finally, in the third scheme, the Antiicing Valve gets 3 spares, while all the other components get the same number of spares as in the first scenario.

Figure 16 shows the system unavailability curves when the residual lifetime prediction of the main fuel pump varies. In this scenario, we apply the same spares allocation scheme as the first one in the first scenario. In the first case, the residual life time of the main fuel pump is derived from its nominal failure frequency, which is approximately 65581 hours. In the other three cases, we assume that based on prognosis, the main pump's residual life time has been updated to 6558, 1312, 656 hours, respectively.

As we can see from Figure 15 and Figure 16, the spares analysis module allows a user to evaluate and compare different candidate spares allocation schemes, predict the system availability trend and select the spares allocation scheme with the highest system availability and within the budget constraints. Moreover, the system availability prediction is updated whenever the residual life time estimate for any component in the system based on prognosis is changed, which allows one to predict future spares usage and make proactive asset management decisions.

5. CONCLUSION

In this paper, an integrated model-based prognostic process was applied to predict the residual life time of a generic centrifugal pump system. In this process, we used singular perturbation methods of control theory, coupled with dynamic state estimation techniques. An IMM filter was employed to estimate the degradation measure and the time-averaged mode probabilities are used to predict the residual life time. The residual life prediction can be used for demand forecasting and hence assist in spares allocation and inventory management. A "smart services" solution supported by diagnostics and prognostics was also presented, which integrates maintenance and inventory management with system operating conditions and health information collected and inferred by a diagnosis and prognosis server. A case study was conducted to demonstrate the process of updating the system availability analysis results using the residual life estimates from prognosis and assessing the efficacy of different spares allocation schemes in maximizing system availability.

There are several future extensions to this research work. These include handling multiple degradations in the prognosis process, application of the prognosis and spares allocation assessment processes to real-world systems, and optimization of spares allocation using evolutionary approaches.

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